An Enhanced Non-Linear Adaptive Filtering Technique for Removing High Density Salt-and-Pepper Noise

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ABSTRACT
This paper presents an enhanced non-linear adaptive filtering technique for removing high density salt-and-pepper noise from digital images. The proposed filtering technique integrates statistical analysis of local features with a median-based noise adaptive filter, which differentiates the corrupted and uncorrupted pixels and processes only the corrupted ones in order to preserve the fine details of the image. The adaptive behavior of this filter enables it to adjust the filtering window based on the local noise density and facilitates the estimation of noise-free median values. Moreover, while most of the existing filters simply replace a corrupted pixel with the average or median of the last processed pixels when the maximum window size is reached, the proposed technique employs further statistical analysis to obtain a more accurate correction term. Experimental results show that, the proposed technique performs better than some state-of-the-art non-linear filters, suppressing noise level as high as 95%, while preserving signal-to-noise ratio, visual quality and necessary details.

General Terms
Image Processing.

Keywords
Impulse noise, salt-and-pepper noise, adaptive median filter, enhanced non-linear adaptive filtering.

1. INTRODUCTION
Impulse noise is a special type of noise where the intensity of the corrupted pixels has the tendency of being either relatively high or low [1]. The principal sources of impulse noise in digital images arise due to transmission errors, faulty memory locations or timing errors in analog-to-digital conversion [2]. Salt-and-pepper noise, a special case of impulse noise is the phenomenon where a certain percentage of individual pixels of an image are randomly digitized into the two extreme (maximum and minimum) intensities in the dynamic range [3]. It is named 'salt-and-pepper' because of its appearance as white and black dots superimposed on the corrupted image [4]. The information or data that was present in the original image may be damaged severely under the presence of salt-and-pepper noise. Therefore, removal of this type of noise is critical for the extraction of reliable and accurate information from a digital image. Since linear filtering techniques tend to blur the edges and perform weakly under the presence of salt-and-pepper noise, nonlinear filters have been widely exploited due to their superior performance in removing this type of noise and also preserving the fine details of the image.

Windowing the noisy image with the Standard Median Filter (SMF) is the simplest way to remove salt-and-pepper noise. However, in this approach, as the value of each pixel is replaced by the median of the gray levels in the neighborhood of the corresponding pixel [4] regardless of whether it is corrupted or not, the SMF is ineffective in presence of high density noise and exhibits blurring of the filtered image if the window size is large [2]. For noise level over 50%, it fails to preserve the edge details of the original image [5]. Different methods have been proposed to improve the performance of median filtering, such as the Weighted Median Filter (WMF) [6], the Center Weighted Median Filter (CWMF) [7], and the Recursive Weighted Median Filter (RWMF) [8], where weights are assigned to selected pixels in the filtering window in order to control the filtering behavior. However, these filters process all the pixels of an image without considering whether the current pixel is corrupted or not. In addition, local features of the image such as the possible presence of edges are also ignored [9]. Therefore, when the noise level is high, these filters fail to recover the details and edges satisfactorily [9].

In this context, the ideal approach is to process only the corrupted pixels of an image while filtering, without changing the uncorrupted pixel values. Some non-linear filtering techniques, such as the Adaptive Median Filter (AMF) [10], the Tri-State Median Filter (TSMF) [11], the Progressive Switching Median Filter [12], the Multi-State Median Filter (MSMF) [13], and the Noise Adaptive Soft Switching Median Filter (NASSMF) [14] apply noise detection process to discriminate between corrupted and uncorrupted pixels. Thus, only the corrupted pixels are selected for processing while the noise free pixels are left unchanged in the filtering stage. These techniques can effectively remove low to medium density salt-and-pepper noise.

Recently, a Decision Based Algorithm (DBA) [2] has been proposed, where only noisy pixels are replaced by the median value or by the mean of the previously processed neighborhood pixel values. However, at higher noise densities, it is likely that the median value is also a noise. Therefore, this method produces streaking when the noise density is high [9]. In [9], a Non-linear Adaptive Statistics Estimation Filter has been proposed to remove high density salt-and-pepper noise, which reduces streaking at higher noise densities. A two-stage Noise Adaptive Fuzzy Switching Median filter (NAFSM) has been proposed in [3], where the noise detection stage utilizes the histogram of the corrupted image to identify the noise pixels first. Then, the second stage of filtering process employs fuzzy reasoning to process the noise pixels only. Thus, this method handles the uncertainty present in the extracted local information, which was introduced by noise [3]. More recently, the modified decision based unsymmetric trimmed median filter (MDBUTMF) [15] has been presented, where pixel values of a local neighborhood are trimmed asymmetrically in order to remove salt-and-pepper noise.

In this paper, we have proposed an enhanced median-based adaptive filtering technique for the removal of high density salt-and-pepper noise. The proposed filtering method employs a combination of noise adaptive median filter and local statistics-based estimation in order to process only the corrupted pixels of an image. The adaptive behavior of this filter enables it to adjust the filtering window based on the local information (e.g. noise density) of the image and thus make it possible to avoid selecting a noisy median value. Moreover, applying the statistical analysis of the local features helps to estimate an accurate correction term under the presence of high density salt-and-pepper noise. The proposed technique shows effective filtering performance across a wide range of noise density varying from 10% to 95%. Moreover, it preserves the fine details and textures contained in the original image satisfactorily.

2. ADAPTIVE MEDIAN FILTER (AMF)

The Adaptive Median Filter (AMF) is an enhanced median-based filtering technique, which overcomes the shortcomings of the Standard Median Filter (SMF). The basic difference between the AMF and the SMF is that, the AMF changes the window size during the filtering operation, depending on the noise density of the image. The variation of this window size depends on the median value of the gray-levels in the local neighborhood. The AMF starts with a 3×3 window and checks the value of the median in the corresponding neighborhood. If the median value is found to be an impulse, then the window size is increased and the process is repeated until a noise-free median value is found or the size of the filtering window reaches a threshold. The AMF filtering algorithm works in two levels, denoted as level *A* and level *B*:

S_{xy} = Processing Window Size
Z_{min} = Minimum Gray-level Value in S_{xy}
Z_{max} = Maximum Gray-level Value in S_{xy}
Z_{med} = Median of Gray-levels in S_{xy}
Z_{xy} = Gray-level at Coordinates (x, y)
S_{max} = Maximum Allowed Size of S_{xy}

Level *A*: $A1 = Z_{med} - Z_{min}$
$A2 = Z_{med} - Z_{max}$
if $A1 > 0$ and $A2 < 0$, go to level *B*
else increase the window size
if window size < S_{max}, repeat level *A*
else output Z_{xy}

Level *B*: $B1 = Z_{xy} - Z_{min}$
$B2 = Z_{xy} - Z_{max}$
if $B1 > 0$ and $B2 < 0$, output Z_{xy}
else output Z_{med}

3. PROPOSED METHOD

The proposed filtering technique processes only the corrupted pixels in order to preserve the fine details and textures that are contained in the original image. Therefore, when a pixel with the maximum or minimum intensity value (0 or 255 in case of 8-bit gray-scale image) is detected, only that pixel is subjected to the filtering process. Otherwise, the pixel value is retained and the filtering window moves to the next pixel position.

The filtering algorithm works in two levels, namely adaptive median-based filtering and statistics-based estimation. At the adaptive median-based filtering stage, the algorithm attempts to detect a noise-free median value from the corresponding neighborhood of the corrupted pixel in order to replace its value with the median. If it fails to obtain a noise-free median value, then the corrupted pixel is subjected to further processing and a correction term is obtained through the statistical analysis of the local neighborhood.

3.1 Adaptive Median-Based Filtering

Given an image *X* corrupted with salt-and-pepper noise, the proposed filter employs a square processing window $W_{2d+1}(i, j)$ with odd $(2d+1)\times(2d+1)$ dimensions centered on a corrupted pixel (i, j) and calculates the median from the corresponding neighborhood. Formally, the processing window can be defined as

$$W_{2d+1}(i, j) = X(i+a, j+b), \quad \text{where } a, b \in \{-d, ..., 0, ..., d\} \qquad (1)$$

The algorithm starts with d=1, and checks whether the median of the local neighborhood is noise-free or not. If a noise-free median is found, then the value of the corrupted pixel (i, j) is set to be equal to the median value. On the other hand, if the median value is noisy (0 or 255), the processing window is expanded by incrementing the value of *d* by 1, and the algorithm again checks for a noise-free median value in the corresponding neighborhood. This process is repeated until a noise-free median is found or the size of the processing window reaches a pre-defined maximum window size (d=3).

If a noise-free median is found, the corrupted pixel is replaced by this value. Otherwise, the corrupted pixel is subjected to further statistical analysis of the local neighborhood in order to estimate an accurate correction term.

3.2 Statistics-Based Estimation

This part of the algorithm estimates a correction term for a corrupted pixel (i, j), only if no noise-free median value is found in the adaptive filtering stage though the maximum window size is reached. This can happen when the noise density in the local neighborhood is too high (all the pixels are corrupted) or the image itself contains local regions with minimum or maximum intensity value in the dynamic range. To facilitate the decision of whether the current pixel is a noise or part of a region originally having the maximum or minimum intensity value, the proposed algorithm checks the value of the last processed pixel.

If the value of the last processed pixel is not 0 or 255, then the current pixel is considered as a noisy pixel. However in this case, simply using the last processed pixel to replace the noise pixel may not be consistent with the property of the local region.

In order to ensure the preservation of fine details and textures, the proposed method first checks the property of the region defined by a window of size 9×9. If a noise-free median is found in the neighborhood defined by this processing window, then it can be said that, replacing the noise pixel with the last processed pixel value will result smooth transition. Therefore, when a noise-free median is found in the larger window, the noise pixel is replaced by the last processed pixel. Otherwise, the noise pixel is replaced by the mode of the local neighborhood.

On the other hand, if the value of the last processed pixel is 0 or 255, then the local region is considered to have the maximum or minimum value in the dynamic range as a property of the original image. In this case, the mode of the local 3×3 neighborhood is used as the correction term. The use of mode in this stage facilitates preserving smooth transitions in the restored image. Fig 1 illustrates a flowchart of the proposed algorithm.

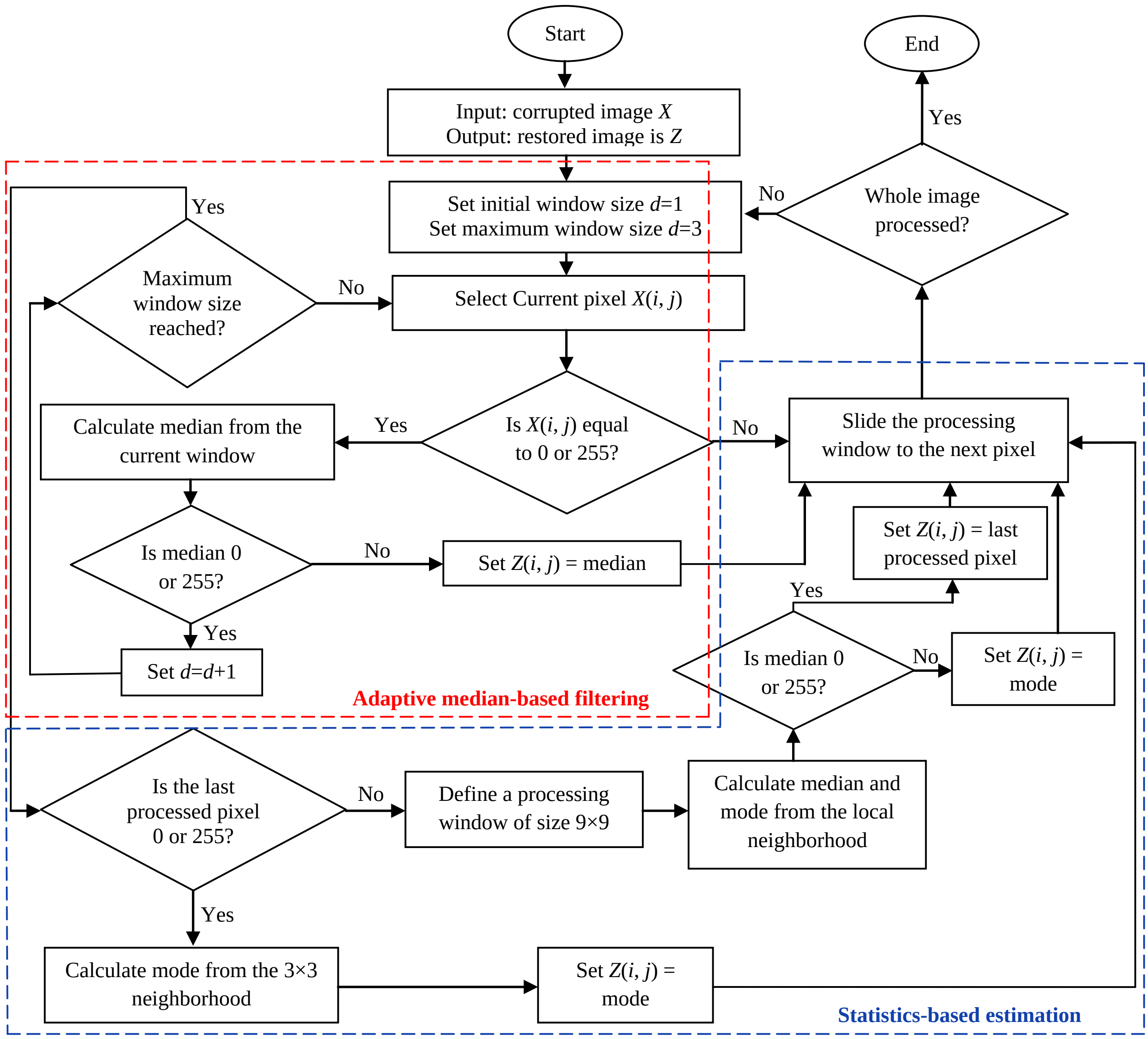


Fig 1: Flowchart of the proposed filtering method

4. EXPERIMENTAL RESULTS

The performance of the proposed algorithm is tested with different grayscale and color images. The Peak-Signal-to-Noise Ratio (PSNR), Mean Absolute Error (MAE), Mean Square Error (MSE), and Image Enhancement Factor (IEF) evaluation schemes are used to quantitatively assess the strength and quality of the restored images, where

$$PSNR = 10 \times \log_{10}\left(\frac{255^2}{MSE}\right)$$

(2)

$$MSE = \frac{1}{MN}\sum_{i,j}(y_{ij} - x_{ij})^2$$

(3)

$$MAE = \frac{1}{MN}\sum_{i,j}| y_{ij} - x_{ij} |$$

(4)

$$IEF = \frac{\sum_{i,j}(X(i,j) - Y(i,j))^2}{\sum_{i,j}(Z(i,j) - Y(i,j))^2}$$

(5)

Here, *X* denotes the original image, *Y* denotes the corrupted image, *Z* is the restored image, and *MN* is the total number of pixel in the image. In our experiment, a total of 7 standard test images (Lena, Baboon, Bubble, Barbara, Cameraman, Fishing boat, and Pepper) frequently used in literature are selected and contaminated with salt-and-pepper noise ranging from 10% to 95%. This set of standard test images contains various characteristics, which is suitable for testing filtering performance.

The performance of the proposed algorithm (PA) is compared with some state-of-the-art non-linear filters, namely the AMF [10], the DBA [2], the NAFSMF [3], and the MDBUTMF [15] filter. Table 1-4 shows the performance comparison of different algorithms for Lena image corrupted with varying noise density.

Table 1. Comparison of PSNR values of different algorithms for Lena image at different noise densities

Noise in %	Peak-Signal-to-Noise Ratio (dB)					
	AMF	SMF	DBA	NAF SMF	MDBU TMF	PA
10	33.9	41.8	31.7	42.6	37.6	43.4
20	29.6	37.2	29.3	38.7	34.3	39.6
30	24.1	34.3	26.5	36.3	32.5	36.9
40	19.1	32.1	23.6	34.3	31.1	35.1
50	15.3	29.9	21.1	32.5	29.8	33.5
60	12.3	27.4	19.0	30.8	27.4	31.9
70	9.9	22.2	17.3	29.3	23.9	30.4
80	8.0	16.3	15.5	27.4	19.7	28.6
90	6.5	10.5	13.7	23.7	15.4	26.0

Table 2. Comparison of MAE values of different algorithms for Lena image at different noise densities

Noise in %	Mean Absolute Error					
	AMF	SMF	DBA	NAF SMF	MDBU TMF	PA
10	2.7	0.4	1.6	0.4	0.6	0.3
20	3.4	0.9	2.2	0.8	1.3	0.7
30	4.9	1.5	3.4	1.3	1.9	1.2
40	8.9	2.2	5.4	1.8	2.5	1.7
50	16.7	3.0	8.5	2.4	3.2	2.2
60	29.2	4.1	12.5	3.1	4.2	2.8
70	47.4	6.8	17.7	4.0	6.3	3.6
80	70.9	15.1	25.3	5.1	11.6	4.7
90	98.1	43.3	36.1	7.5	24.7	6.4

Table 3. Comparison of MSE values of different algorithms for Lena image at different noise densities

Noise in %	Mean Square Error					
	AMF	SMF	DBA	NAF SMF	MDBU TMF	PA
10	26.0	4.3	43.9	3.6	11.3	2.9
20	71.1	12.5	77.0	8.8	24.1	7.2
30	254.4	24.4	146.4	15.4	36.5	13.0
40	803.9	40.3	282.6	24.3	50.1	20.2
50	1940.8	65.5	510.7	36.4	68.8	29.4
60	3816.8	119.2	814.0	54.2	119.6	41.3
70	6619.5	388.0	1215.8	75.8	266.7	59.1
80	10255.9	1541.9	1837.7	118.4	703.1	89.0
90	14496.3	5845.9	2783.5	276.2	1880.3	162.0

Table 4. Comparison of IEF values of different algorithms for Lena image at different noise densities

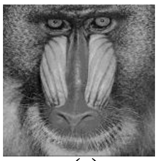
Noise in %	Image Enhancement Factor					
	AMF	SMF	DBA	NAF SMF	MDBU TMF	PA
10	73.6	443.2	43.5	529.3	169.9	649.8
20	53.1	302.7	49.0	431.0	156.7	523.5
30	22.2	231.5	38.6	366.6	154.9	434.7
40	9.5	189.6	27.1	314.5	152.6	377.9
50	4.9	145.4	18.6	261.3	138.3	323.9
60	2.9	95.8	14.0	210.5	95.5	276.4
70	2.0	34.4	10.9	176.1	50.0	225.9
80	1.5	9.9	8.3	128.9	21.7	171.4
90	1.2	2.9	6.2	62.2	9.1	105.8

From the experimental results, it is evident that, the proposed filtering method performs better than existing non-linear filtering algorithms at both low and high noise densities. Table 5 shows a performance comparison of the proposed method against the existing methods in terms of PSNR with different images corrupted with 90% salt-and-pepper noise.

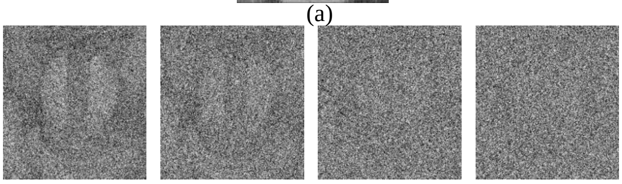
Table 5. Comparison of PSNR values for different images at 90% salt-and-pepper noise

Test images	PSNR in dB					
	AMF	SMF	DBA	NAF SMF	MDBU TMF	PA
Lena	6.5	10.5	13.7	23.7	15.4	26.0
Baboon	6.7	10.2	13.9	18.2	15.2	19.1
Bubble	4.2	3.5	6.1	4.6	6.4	5.9
Barbara	6.4	10.2	14.0	20.2	14.6	21.2
Cameraman	6.3	10.2	12.9	21.7	14.4	23.4
Fishing boat	6.7	10.7	13.7	23.8	16.3	27.5
Pepper	6.2	9.9	13.1	23.3	14.0	25.6

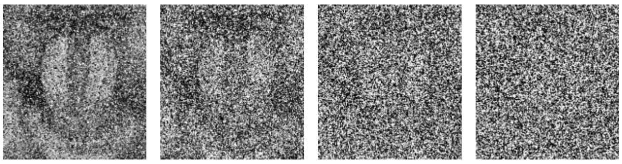
In addition, visual inspection is performed on the filtered images in order to judge the effectiveness of different algorithms in removing salt-and-pepper noise. The qualitative analysis of the proposed algorithm against the existing algorithms at different noise densities is shown in Fig. 2.



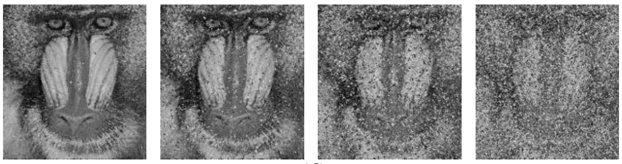
(a)



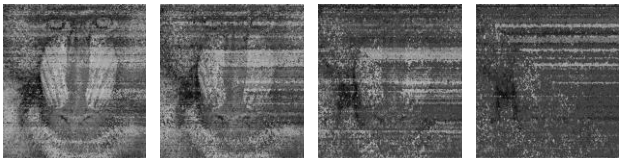
(b)



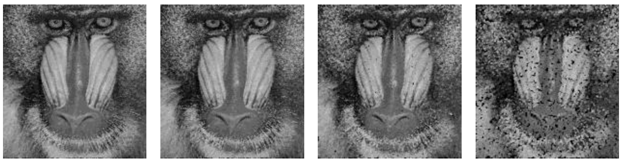
(c)



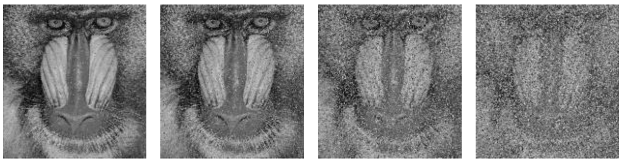
(d)



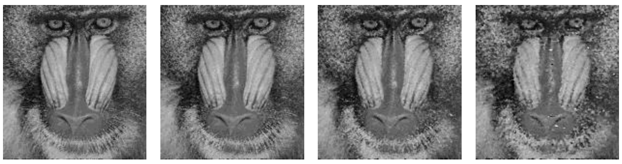
(e)



(f)



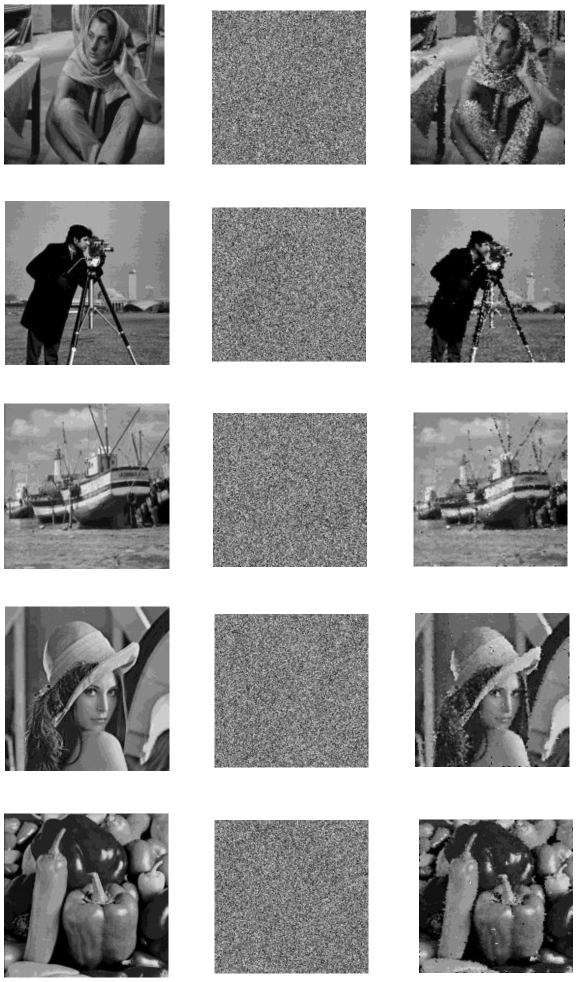
(g)



(h)

Fig 2: Results of applying different filtering methods on Baboon image corrupted with salt-and-pepper noise. Here, (a) is the original image and (b) shows images corrupted with 70%, 80%, 90%, and 95% salt-and-pepper noise, respectively from left to right. Row (c), (d), (e), (f), (g), and (h) shows the results obtained by using SMF, AMF, DBA, NAFSMF, MDBUTMF, and PA, respectively on the corrupted images of (b)

From Fig. 2, it can be observed that, the quality of the restored images using the proposed algorithm is better than the restored images using other existing algorithms. Fig. 3 shows the restored images obtained by applying the proposed filter on different images corrupted with high density (95%) salt-and-pepper noise.



(a) (b) (c)

Fig 3: Results of applying the proposed filter on different images at a noise density of 95%. Column (a) shows the original images, (b) shows the images corrupted with 95% salt-and-pepper noise and column (c) shows the restored images using the proposed algorithm

The performance of the proposed filter is also evaluated for color images. Fig 4 shows the result of applying the proposed filter on Lena image corrupted with varying noise densities.

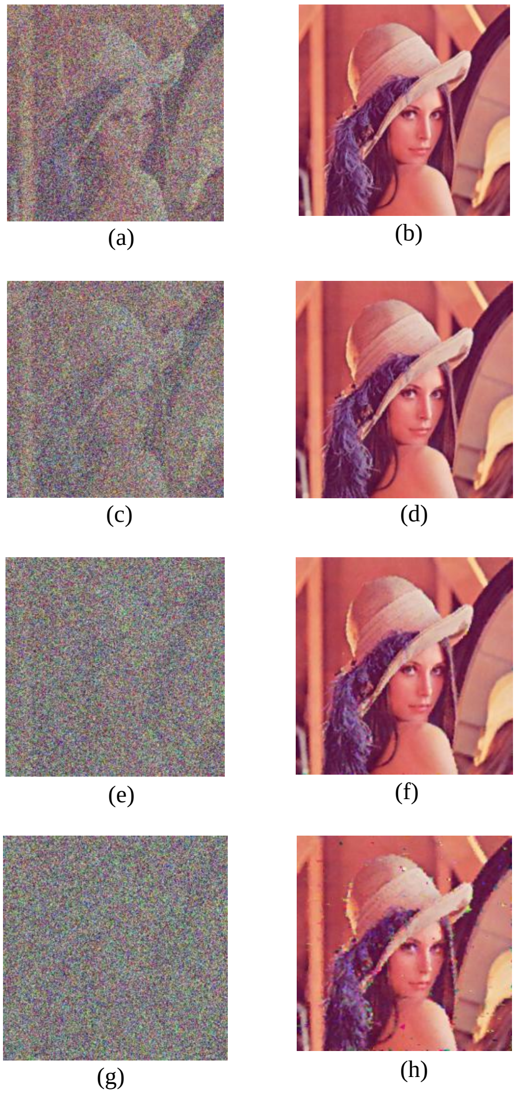


Fig 4: Results of applying the proposed filter on a color image corrupted with varying density salt-and-pepper noise, (a), (c), (e), and (g) shows the Lena image corrupted with 70%, 80%, 90%, and 95% noise, respectively and (b), (d), (f), and (h) shows the results of applying the proposed filter on images of (a), (c), (e), and (g), respectively.

5. CONCLUSION

In this paper, a new filtering algorithm is proposed that gives superior performance in comparison with different existing noise removal algorithms, such as SMF, AMF, DBA, NAFSMF, and MDBUTMF in terms of PSNR, MAE, MSE, and IEF. The performance of the proposed method is tested with a set of standard test images frequently used in literature contaminated with salt-and-pepper noise of varying densities. The superiority of the proposed method is due to the integration of a local statistics-based estimation method with an adaptive median-based filtering technique, which facilitates the estimation of an accurate correction term at high noise densities. Therefore, the restored images provide the best qualitative and quantitative measures.

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